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Long-term wind resource and uncertainty estimation using wind records from Scotland as example

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Abstract

A systematic analysis of the sensitivity of a wind turbine's output to changes in observed wind statistics between different sites in Scotland over available wind records of up to 43 years length was performed. The analysis was performed in the context of observed variability on time scales longer than a year. The findings are discussed in the context of the ability to predict the long-term wind energy potential reliably both for wind farms as well as small turbines. In the analysis, some measures are defined to quantify the forecast accuracy and the long-term prediction error. One of the items of discussion was motivated by the observation in the wind industry that the year 2010 was a poor year, with hopes that it was just an exceptional year and fears that it might be an indicator of continuing climate change. The result of this discussion is that 2010 can only be seen as an outlier if one assumes that the past decades represent a constant wind climate. A linear regression, however, suggests that this assumption may not be correct and that 2010 may have been a low-wind year but consistent with generally observed fluctuations around a changing wind climate.

Keywords: wind energy, wind resource, wind resource prediction, climate change

1. Introduction

Wind power generation is one of the fastest growing industries in the developed world, with an installed capacity of 194 GW in 2010 through large wind farms, projected to grow by 15 - 23% per year [1] over the next 5 years. Considering that some of the wind farms now reach an installed capacity in the GW range, even a small reduction in output can amount to a significant change in income. For example, the year 2010 was found to be significantly less windy than the long-term average, and the electricity output from wind farms was less than anticipated with a noticeable reduction in income for the wind farm operators. If, as an illustration, a wind farm with an installed capacity of $G = 100$ MW is expected to operate at a capacity factor of $C_C = 30\%$, its Annual Electricity Production, AEP, is $AEP = C_C G \times 8760$ h/year $= 262.8$ GWh/year. A reduction in the capacity factor by one percentage point to $C_C = 29\%$ would lead to a reduction in the AEP by 8.8 GWh. With a sale price of, say, 12p per kWh, this would result in loss of expected income of around £1 million. As a result, wind farm operators are concerned with predicting the wind a few hours ahead for operational purposes, e.g. [2], or a few months ahead for planning, e.g. [3]. On a national level, it is not only the wind farm's output but also the instantaneous matching of wind power to demand and other generation that is an important factor for a reliable electricity provision. Depending on the correlation between wind and demand, a network may be able to incorporate a lesser or greater contribution from wind. A study analysing 12 years of wind and demand data from the UK [4], for example, found that not only the fluctuations in the residual demand to be met from (fossil) responsive generation are very large but also that there are some winter-time weather systems which result in very low wind power at times of very high peak demand.

In addition to the strong development of increasingly large wind farms there is substantial interest in smaller turbines, partly motivated by individual interests and partly by governments' aims to reduce their carbon emissions through diversified centralised and distributed generation. Guided by these aims, governments often provide grants or subsidies to install small-scale renewable systems at a building or community level, e.g. [5]. A survey of 215 small wind turbines in the UK, all with rated output of between 1 kW and 1.2 kW and most mounted on buildings [6], has shown that the electricity production from these small turbines is extremely sensitive to the local wind conditions. Furthermore, a systematic CFD analysis demonstrated how sensitive the turbine's output is to its exact mounting position on the roof [7]. Very few of the turbines surveyed in Ref. [6] produced more than a few percent of their full potential. A review on methods of estimating the urban wind resource for building mounted turbines [8] highlighted, among a few other issues, that

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the use of typical distributions, such as the Weibull distribution introduces large errors as the local environment affects the local wind substantially. Equally, the use of annual average mean measures, such as the widely available NOABL database for the UK[1], consistently overestimates the actual resource at the site of the wind turbine, e.g. [5, 9].

Numerous wind energy resource assessments have been carried out over the years, e.g. [10, 11]. A common assumption is to describe the annual wind statistics by a Weibull distribution, e.g. [12], though experience has shown that this is not always the most appropriate distribution, and alternatives have been proposed and discussed, e.g. [13, 14, 15]. While reasonably exposed sites in many parts at mid-latitudes, such as most of Europe, can usually be approximated by a Weibull or log-normal distribution, the same cannot be said in the urban environment or in other climatic zones. In Asia and the Indian sub-continent, for example, one frequently finds sites which show a bi-modal wind speed distribution [16]. How sensitive the actual electricity generation is to choosing the best distribution function is still uncertain but this particular question is not an aim of this study.

Going beyond a simple mean resource description, a 33-year analysis of UK wind data [17] assessed the variability of the expected and reported wind power capacity over this period. This analysis identified an inter annual variability of 7.4% around a long term mean capacity factor of 0.3 for the UK, a seasonal variation of 30% around that mean, and a daily cycle of magnitude of around 10%. Still, this study, and all others referred to here, implicitly assumed that the mean wind resource derives from a stationary climate, at least over the analysis period and a reasonably long future to be appropriate for projected wind farms.

However, with climate change as a key part in the energy debate, it is becoming increasingly important to assess how the wind resource might change as the climate changes. Few wind farms have operated consistently over the time scales associated with climate change and one has to resort either to wind speed data from individual meteorological stations, to the output from climate models, or a climate data basis compiled from meteorological information. The resolution of global climate models with some 100s of km resolution are too coarse to be directly applicable for wind energy purposes and the results have to be scaled down to an appropriate resolution, which can be done through dynamic downscaling using regional climate models or through statistical downscaling [18]. The UK Climate Impacts Programme provided data with a 50 km resolution [19] based on regional climate models for climate projections up to 2100. This future climate data base is complemented by a climate history for the UK covering the period form 1961 to 2000 compiled from UK Meteorological Office surface stations[20].

The UKCIP02 predictions were used for an initial assessment of the magnitude of this issue for the UK wind prospects [21] with indications that there might be very slight changes on the annual UK resource but that this masks somewhat stronger regional changes and substantial seasonal changes for the different regions within the UK. In particular, the indications were that winters would become windier and summers less windy everywhere except the North of Scotland with almost the opposite trend, and that Northern Ireland would experience a much stronger reduction in the summer resource than the rest of the UK.

Climate predictions from the IPCC are also being used to assess the future of the wind resource over the world, e.g. [22]. Due to the uncertain nature of the climate predictions and subsequent downscaling, such results have to be interpreted with a certain degree of caution.

Rather than using climate predictions, Pryor et al. [23, 24] used 43 years of re-analysis data sets from a coupled atmosphere-ocean general circulation model and dynamical downscaling with regional climate models for the Baltic Sea. This suggested that the climate and the wind resource has changed and mostly increased from 1958 to 2001. Similar approaches using IPCC predictions as well as re-analysis and dynamical downscaling through regional climate models for four chosen sites in California [25] highlighted the variation in results from different methodologies. Statistical downscaling, as opposed to dynamical downscaling, can be more reliable as the downscaling process is based on actual observations rather than imposed models. This was successfully demonstrated for a region in the US applying a tree-structured regression (TSR) model, which is a type of classification analysis, for current and future climates [26]. Similar to the UK prediction [21] the results indicate a noticeable reduction in spring and summer months but the winter results were not conclusive. Another promising statistical approach is the use of empirical downscaling functions, such as empirical orthogonal function (EOF) analysis [27].

Direct wind observations have only most recently been used to investigate the link between climate and wind power. Given the length of direct and continuous data available, the first studies investigated the link between local wind and climate indicators with a clear variability of a few months. A recent study has correlated the hourly observed wind speed and expected power outputs from two sites, one in the North-West of England and one on the outer Hebrides in the North-West of Scotland against the North-Atlantic Oscillation index, one of the main climate indices [3]. The results confirmed the hypothesis that the NAO index is reflected in the local wind statistics.

A study co-current with our work presented a detailed analysis of wind data at a selection of surface stations covering the entire UK [28][2]. A record compiled from seven

[1] UK Department of Energy and Climate Change: http://www.decc.gov.uk/en/content/cms/meeting_energy/wind/, accessed 30.Sept. 2011

[2] A full publication of this study by P. Kritharas and S. Watson is currently under review for *Wind Energy*

suitable weather stations between 1958 and 2006 did not show any significant trend in the data whereas the UKCIP02 did show a much stronger trend to lower wind speeds. Watson and Kritharas [28] attribute this to the fact that the UKCIP02 dataset included many surface stations which have become more sheltered as the surrounding land was developed or trees grew taller. The seven sites chosen for their analysis were carefully selected to avoid this effect. Furthermore, they identified that the precise height of the anemometer above ground could vary by a few metres and affect the readings noticeable. In response, their data were height-corrected to the nominal anemometer heigh of 10 m above ground using a logarithmic wind shear profile for all sites. To obtain regional statistics, they used a shorter period between 1983 and 2008 for which they could identify 60 suitable stations. Similar to the UKCIP02 based predictions, they observed a regional split, with an observed increase in the annual mean wind index in the South East against against a general decrease in the other parts of the UK with the strongest decrease in the North West. A question arises, as to whether these regional 25-year trends would extend to the longer periods. To address this question at least for one region, our study extends the analysis to seven selected stations in one specific region.

The three aims of this study are (a) to analyse the expected electricity production for a typical wind turbine using hourly wind measurements at seven sites in Scotland, (b) to identify any long-term trend in that production reflecting possible climate change at this regional scale, and (c) to calculate measures of prediction uncertainty for wind resource predictions based on past measurements alone.

To address these aims, we will first introduce the data set of wind measurement records from seven UK Meteorological Office surface stations situated in a fairly narrow latitude range in Scotland including the Glasgow-Edinburgh latitude, where the sites were chosen to represent all typical situations in that region, from coastal sites exposed to the Atlantic to sheltered suburban sites. The annual and decadal variation will be analysed, both in terms of the wind speed and as the capacity factor which an idealised wind turbine would achieve in those conditions either at the height of the anemometer of 10 m above ground, representative of a small turbine (1 to 10 kW), or at an extrapolated height of 80 m which is representative for large wind turbine with a rated power in the MW range.

2. Methodology

2.1. Wind speed data

Seven surface stations in Scotland were chosen from the UK Met. Office - MIDAS Land Surface Stations [29] as listed in Table 1 and indicated in the map of Scotland in Figure 1. All sites use anemometers at a height of 10m above ground in 'open terrain' which is defined as an area

Figure 1: Map of Scotland with indicators of the sites, starting with site A at the left and continuing to site G at the right, using their label as defined in Table 1 [source: © Google].

where the distance between the anemometer and any obstruction is at least 10 times the height of that obstruction. The data set records the hourly mean wind during the hour preceding the time stamp of the record. The hourly mean wind speeds are stored to the nearest knot (1kn = 0.5144m/s). For the analysis, the hourly wind speeds were converted to m/s, and the uncertainty in each measurement was assumed to be ±0.5kn = ±0.257m/s.

All sites sit within a small latitude belt but span the breadth of central Scotland and represent a range of typical settings for that region, ranging from coastal to sheltered inland. The setting and length of the record are summarised in Table 1. A first test of the pair-wise cross-correlation, shown in Table 2, gave the expected result that neighbouring sites were well correlated with correlation coefficients between $r = 0.67$ and 0.84 with either zero or one-hour lag. This reduced to a smallest coefficient of 0.52 between the western most site (Port Ellen) and the eastern most (Blackford Hill) with a time lag of three hours. The range of time lags for best correlation between two sites is consistent with the prevailing wind from an approximately south-westerly direction.

2.2. Extrapolation of the wind to different heights above ground

For the analysis, the MIDAS data were used directly directly or extrapolated using a standard wind shear assumption. The direct measurements 10 m above ground are representative for well-sited small wind turbines. As

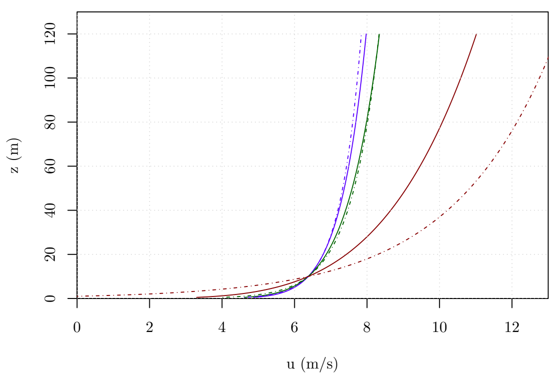
Table 1: Summary of Met. Office stations used in the analysis with their location in decimal degree and elevation above sea level. Latitude and longitude in degree, elevation in metres above sea level.

	Station Name	latitude	longitude	elevation	type	Start
A	Port Ellen	55.6813	– 6.24866	17	island off west coast	1998
B	Machrihanish	55.4408	– 5.69571	10	west coast, exposed	1969
C	Prestwick Gannet	55.5153	– 4.58343	27	west coast , sheltered	1996
D	Bishopton	55.9068	– 4.53122	59	west, sheltered	1999
E	Salsburgh	55.8615	– 3.87409	277	central, exposed	1980
F	Gogarbank	55.9284	– 3.34294	57	east, sheltered	1998
G	Blackford Hill	55.9228	– 3.18750	134	east, exposed	1976

Table 2: Cross-correlation of wind speeds at selected sites, where the sites are ordered from west to east. Above diagonal are the best correlation coefficients between sites, below are the time lags associated those correlation coefficients.

	PtE	Mch	PIK	Btn	Sal	Ggb	BfH
Port Ellen		0.82	0.69	0.63	0.59	0.55	0.52
Machrihanish	0		0.70	0.61	0.64	0.56	0.59
Prestwick	1	1		0.72	0.76	0.76	0.72
Bishopton	2	1	1		0.67	0.75	0.67
Salsburgh	2	1	0	0		0.73	0.79
Gogarbank	2	2	1	0	1		0.84
Blackford Hill	3	3	1	0	1	0	

a)



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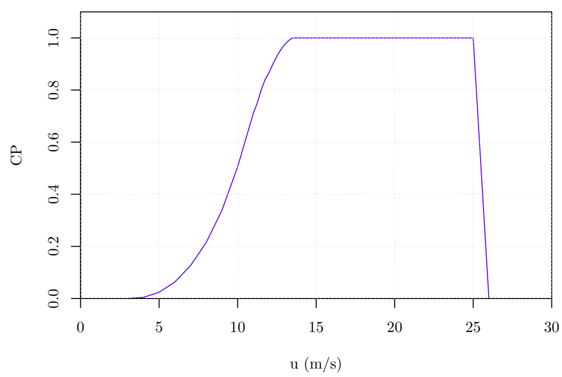

Figure 2: Wind shear profiles – solid lines for power law with blue: $\alpha = 0.09$, green: $\alpha = 0.108$, red: $\alpha = 0.22$; dash-dotted lines for logarithmic profile with blue: $z_0 = 0.2$mm, green: $z_0 = 3$mm, red: $z_0 = 1$m. (a) vertical wind profiles, relative to the long-term mean measured at 10 m above ground at Machrihanish. (b) Performance curve for the assumed wind turbine used in the analysis.

larger wind turbines have a hub height of around 60 to 100m, the reference wind data, U_R, measured at the reference height of $z_R = 10$m can be extrapolated to a height z using a typical wind shear profile [30, 31] of either a logarithmic function or a power law,

$$u(z) = \left(\frac{z}{z_R}\right)^{\alpha} U_R. \quad (1)$$

The power law form was developed in the context of atmospheric stability, where an unstable atmosphere has a typical power law exponent of $\alpha = 0.09$, while a relatively stable atmosphere can be described by $\alpha = 0.22$, shown by the solid lines in Figure 2(a). The wind shear profile of the logarithmic form,

$$u(z) = \left(\frac{\ln z/z_0}{\ln z_0/z_R}\right) U_R, \quad (2)$$

was derived to describe the effect of the surface drag from the surface characteristics and assumes near neutral stability. The surface roughness, z_0, ranges from less than 1mm for off-shore cases to around 1m for complex topography or the urban environment, shown by the dash-dotted lines in Figure 2(a). We chose a logarithmic profile with two choices of roughness length. One profile used a roughness length of $z_0 = 3$mm which is believed to be a good mean representation for reasonably exposed sites. For example, it gives a wind shear profile which is virtually indistinguishable to a power law with $\alpha = 0.108$ which was measured for the off-shore Lillgrund wind farm between Denmark and Sweden [32]. The other case used a roughness length of $z_0 = 300$mm, which is a number close to those recommended for varied land use with trees or some buildings or for forests [33].

2.3. Wind turbine parameterisation

Throughout this paper, the analysis is based on a generic turbine performance curve as representative for the majority of modern large wind turbines, with a cut-in wind speed of 4m/s, a rated wind speed of 12m/s, and a cut-out wind speed of 25m/s, as shown in Figure 2(b). At the rated wind speed, the power output, $P(u)$, reaches the rated power which is here taken as unity, $P_R = 1$. The capacity factor, C_C of the turbine in an environment with a normalised wind distribution, Φ_u, is then simply the convolution integral

$$C_C = \int \Phi_u P(u) du \quad (3)$$

and the Annual Energy Production of a turbine with a rated power of G would be $AEP = C_C\ G \times 8760$h.

Obviously, this approach has a number of implicit assumptions, of which the most critical will be the assumption of an instantaneous response of the turbine to changes in wind speed or direction. In terms of response to changes in wind speed, one could argue that most delays in response to increasing the wind are cancelled by similar delays in response to decreasing the wind, with the one exception of the waiting time for bringing a turbine back into operation after the wind speed has dropped from above the cut-out limit to below. On the other hand, delays in responding to a changing wind direction will always lead to a reduction in the power output compared to that given by the manufacturer.

The errors introduced by the typical performance curve and the implicit assumptions are likely to be small - the performance curves for large turbines look very similar and they are usually sited in relatively clear wind. The same cannot be said for small turbines because their performance curves vary much more between different models and they are sited in much more variable wind conditions. Because of these constraints, the results will be very model- and site-specific and will make it virtually impossible to develop reliable guidelines based on available resources such as weather station data alone.

2.4. Statistical analysis

The analysis of the data was carried out using the statistical package R [34, 35]. For the presentation of data distributions, extensive use of box plots was made, in which the distribution of a quantity around its median is shown in terms of a box and whiskers. For data with no clear outliers the box and whiskers show the range of the observations in their quartiles; the first quartile is represented by the lower whisker, the second by the part of the box below the median line, the third quartile by the part of the box above the median line, and the final quartile by the upper whisker. However, if there are outliers, then they are shown separately, and the whiskers only cover the data which are defined as within the expected range of the distribution. Throughout this analysis, the standard setting for box plots was used which defines the maximum range of the first quartile as 1.5 times the range of the second quartile and similarly the maximum range of the 4^{th} quartile as 1.5 times the range of the 3^{rd} quartile. In box plots where a dark circle is shown within the box, this circle represents the arithmetic mean of the data.

3. Results

While the results presented in this section concentrate on the capacity factors calculated from the hourly measurements and its statistics, the analysis was also applied to calculate wind speed statistics which were then converted to equivalent capacity factors. Furthermore, where only results for a single site were shown, the same analysis was applied to all other sites which all gave qualitatively identical results.

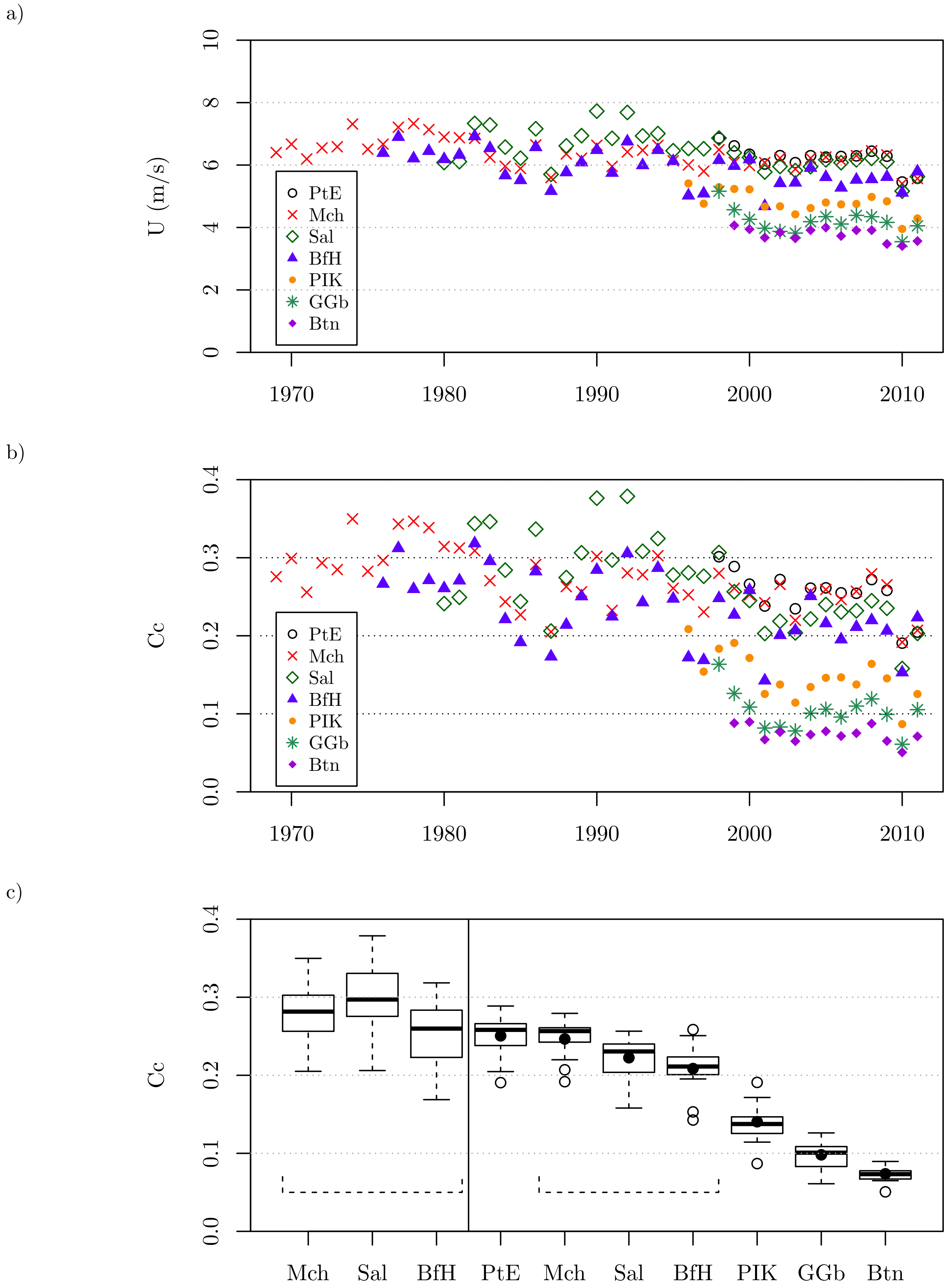

Figure 3: Annual averages of data from all stations. (a) Annual mean wind; (b) Annual capacity factor; (c) Box plots for annual capacity factor from each station. The first three show statistics from before 1999, the remaining seven are all based on the data from 1999 onwards.

3.1. Annual wind speed data from Scotland

This section reviews the wind speed data from the selected seven sites. Figure 3(a) shows the annual mean wind speed directly calculated from the anemometer readings and Fig. 3(b)shows the annual capacity factor from a turbine at the location of the anemometer for all stations over the available measurement period. One can see that the three more exposed sites (which also happen to be the sites with the longer record) cluster around a typical capacity factor of around 0.3 until the mid-90's but then drop to a level between 0.2 and 0.3 since then. An earlier brief period with low capacity factors can be seen for 1984 to 1988 interrupted by a high-wind year in 1986. The most recent exposed side, Port Ellen on the island of Islay, closely follows the other exposed sites during that period. The sheltered sites perform all well below the exposed sites in terms of their electricity production potential. While the graph shows good correlation between different sites and, for example, highlights 1987, 1996, 1997, 2001, and 2010 as low wind years, it is also clear that there is substantial variability across the different sites despite their close proximity and good cross-correlation.

The overall distribution of the annual capacity factor for each station can also be represented by a box plot, figure 3(c), in which the distribution of the capacity factor around its median is shown as a box with whiskers indicating the four quartiles of the distribution. To avoid any bias through low-frequency climate variability, the box plots in figure 3(c) are separated into the period up to 1998 (first three boxes) and the period from 1999 until 2011, for which a complete record for each station exists. There is a clear and statistically significant difference between the ranges for the earlier and later periods from the same three sites for which a longer record exits, where the capacity factor has dropped by between 13% and 26%. For the recent set of results, the stations are ordered in descending mean capacity factor and it is clear that the exposed sites at the West coast are the first in the ranking. Only marginally lower are two exposed sites on hill tops, Salsburgh in the Central Belt between Glasgow and Edinburgh and Blackford Hill in Edinburgh. The final three sites are all low-lying sites near airports, where Prestwick airport is at the coast on the Firth of Clyde but in the lee of the isle of Arran. Gogarbank is near Edinburgh airport while Bishopton is associated with Glasgow airport. The majority of sites show some outliers, where in all sites except Blackford Hill the lowest outlier dates to the year 2010. For both, Salsburgh and Gogarbank, the minimum capacity factor occurred in 2010 but it fell within the permissible range of the whiskers for the box plot.

One useful measure to estimate the variation of the turbine output form one year to the next is the volatility, here estimated as the difference between the capacity factor in one year compared to that from the previous year and then normalised by the current capacity factor. This figure showed very similar behaviour at all sites and only the regional average across all seven sites is shown in figure 4.

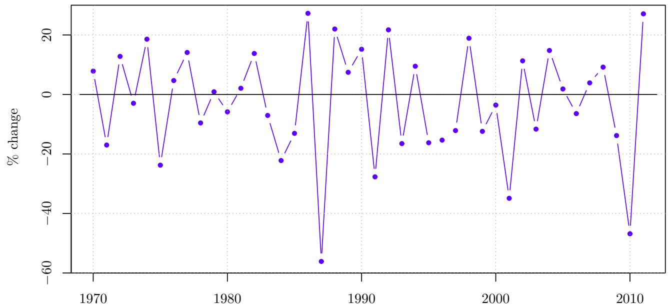

Figure 4: Regional average of the relative change of the annual capacity factor from the previous year.

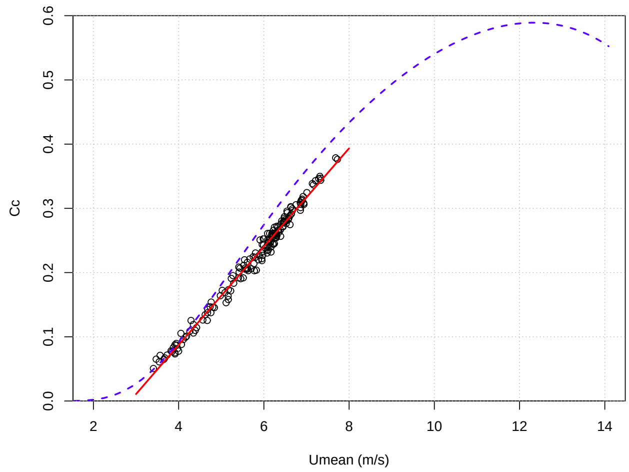

Figure 5: Correlation between annual mean wind speed and annual capacity factor for all stations combined (at 10 m above ground). The dashed line is the capacity factor for a Weibull distribution with the same mean wind speed and a shape factor of $k = 1.6$.

This shows that a typical variation is between 10 and 20%, in fact, the average of the magnitude of this volatility is 15%. It is worth noting that the extreme changes in the negative direction were not compensated by equally strong changes in the positive direction, and the average of the relative change from one year to the next is -2.6%.

Since the measured quantity is the wind speed but the quantity of real interest for the energy supply is the electricity output, the following analysis will contrast the assessment or prediction of the resource in terms of either of these quantities. While these two quantities are, from an instantaneous point of view, related through the highly nonlinear turbine performance curve (Figure 2), the relationship between the annually averaged wind speed and the capacity factor from the hourly wind data depends on the distribution. Since we did not want to impose a distribution, we evaluated the simple correlation between these two quantities, shown in figure 5, and observed that they are extremely well described through a single linear regression valid for all Met. Office stations considered here in the form of

$$C_C = -0.22 + 0.077\,\bar{U} \qquad (4)$$

with quoted uncertainties less than the precision of the coefficients shown here and with an $r^2 = 0.988$ and significance of $p < 10^{-15}$. The goodness of this linear fit is due to the fact that the annual mean wind speeds for all sites and years are within the range where the turbines operate between cut-in and rated power. This is illustrated by showing the capacity factors which would be obtained from a Weibull distribution with a shape factor of $k = 1.6$ and a scale factor to result in the same annual mean wind speed. While the actual shape factor for the different stations and years varied substantially, the value chosen here is commonly found for these sites. The observed capacity factors are consistent with those presented by Sinden [17] in their figure 6. It has to be noted that they suggested a behaviour of the electricity output directly against a turbine power curve, whereas that comparison should have been of the electricity output against an expected electricity output from a mean wind speed, as is presented here. In fact, the Sinden data presented in their figure 6 would make a very good match to the capacity factor derived from the Weibull curve shown here in figure 5.

3.2. Extrapolation to different hub heights

Up to this point, the analysis of the measurements has taken the wind measurements at the anemometer height of 10 m above ground. However, it is clear that the capacity factor is very sensitive to the wind and, from equation (2), that the wind is consistently larger at higher altitudes. We therefore extrapolate the wind speed measurements from the measurement height to a range of heights reached by modern large turbines.

The extrapolation of the 43-year mean capacity factor at Machrihanish using the same wind shear profiles results in similar cases though the change in the capacity factor is much more pronounced at lower heights than the variation in the wind speed. This is most obvious in the profile for the capacity factor in the urban environment in figure 6(b). Figure 6(c) applies the profile most appropriate to the Machrihanish site to convert the extrapolation of the observed wind speeds to capacity factors; this is the logarithmic wind shear profile with $z_0 = 3$mm. One can see that the mean capacity factor rapidly increases from $C_C \sim 0.27$ with a range of ± 0.08 to around 0.37 at 50m height and to 0.4 ± 0.1 at around 80m.

This analysis is extended to the other sites and is summarised in figure 7 as a comparison of the annual capacity factors between the reference height of 10 m (clear boxes) and an extrapolated height of 80 m. For the extrapolation, two wind shear profiles were used to represent off-shore and complex on-shore terrains. The off-shore or near-shore conditions, shown by the grey boxes, used the same surface roughness of $z_0 = 0.3$mm as used in Figure 6(c) while the on-shore conditions, shown by the light-blue boxes, used a surface roughness of $z_0 = 300$mm typical for forestry, for example. To ensure that the comparison across the sites is appropriate, only the wind data from 1999 onwards were used for which all sites provide a continuous record.

Comparing the off-shore wind shear profile first, the three most exposed sites (Port Ellen, Machrihanish and Salsburgh) generally show an increase in the mean capacity factor by 0.13 to 0.14 (which is a relative increase by between 53% and 60%), together with a slight reduction in the variability as turbines find themselves more frequently operating at their rated power. The three sheltered sites Prestwick, Gogarbank and Bishopton increase their mean capacity factor by between 0.07 and 0.10 (or between 68% and 95%). Unlike for the exposed sites, the variability in the annual capacity factor for the sheltered sites increases as turbines are less frequently below their cut-in conditions and more frequently in the part of their performance characteristics which strongly depend on the wind speed. The volatility of the capacity factor is qualitatively identical to that at 10 m above ground, shown in figure 4, but the average annual relative change is reduced from -2.6% to -1.9% and the average magnitude is reduced from 15% to 11%.

Extending this to the rough surface, accentuates this behaviour and in particular the sheltered sites, which are also most likely to have that strong shear profile, benefit most from the increased shear. For example, the sheltered site at Edinburgh airport, Gogarbank, reaches the same capacity factor in the strong shear as the exposed Blackford Hill site in Edinburgh achieves in the low-shear scenario.

3.3. Inter-annual variability of wind and electricity production

As the inter-annual volatility of the capacity even at a good sites for large turbines is around 10% and can even reach 50%, it is clear that a useful prediction of the output should not only result in a prediction but also in a quantification of the confidence in that prediction. In this section, we attempt to quantify the ability to estimate the wind resource in the near future based on past experience from that site alone.

Here we use the data from Machrihanish as it is the longest record from our selection. To estimate the available capacity factor for a given year in the future, we simply use the average from the last few years. The variable parameters in this analysis are the number of years used for the averaging of the past record and the year which is to be predicted. Note that this prediction is for the single year at the specified prediction step rather than the mean for the entire period from the present point to the end of the prediction time. The reason for this was so that it would be possible to identify more clearly at which prediction horizon the reliability of the prediction would deteriorate.

If the prediction of the capacity factor in δt years is the average of the most recent τ years, then the prediction

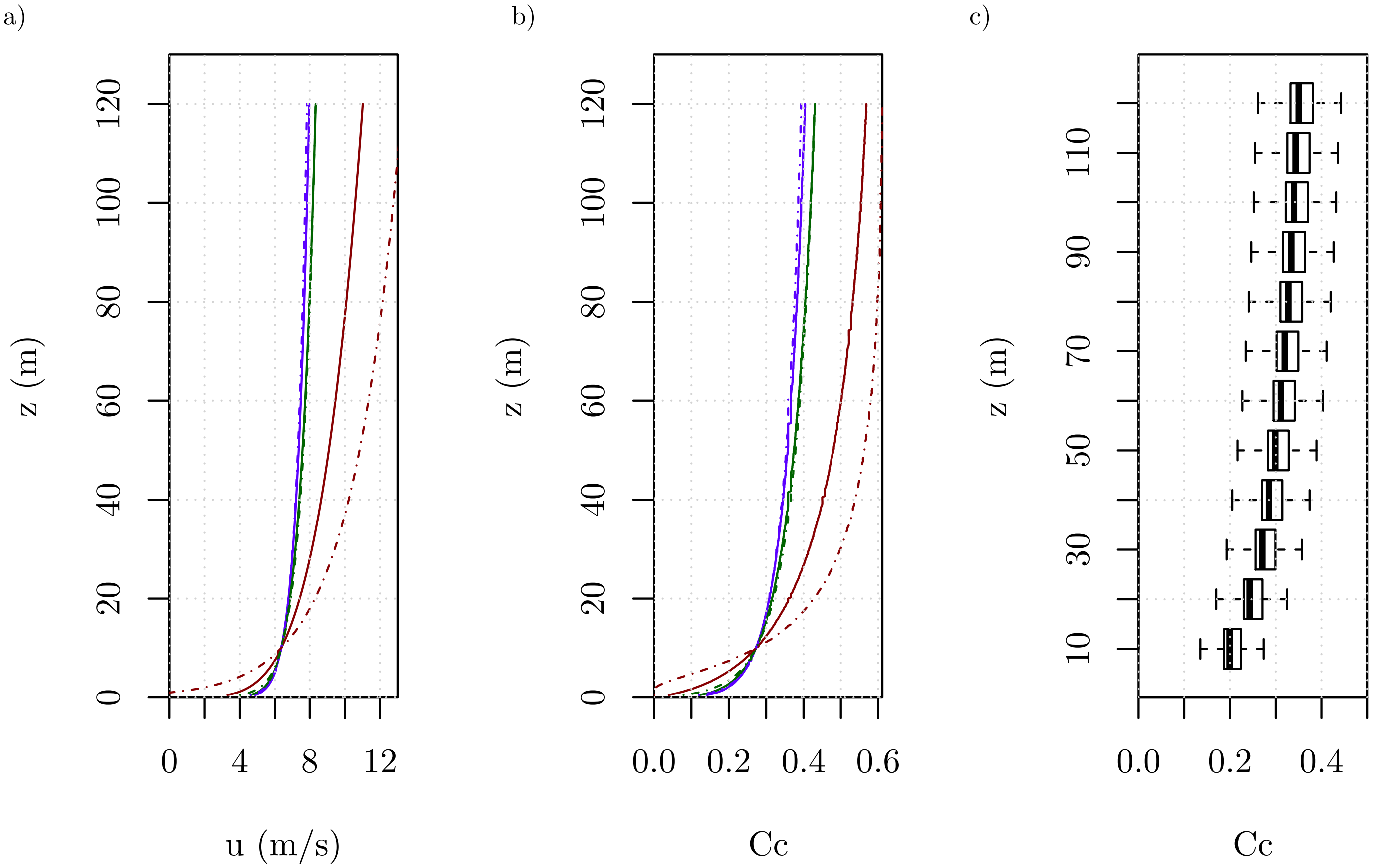

Figure 6: Wind shear profiles and resulting capacity factors relative to the long-term mean measured at 10 m above ground at Machrihanish – solid lines for power law with blue: $\alpha = 0.09$, green: $\alpha = 0.108$, red: $\alpha = 0.22$; dashed lines for logarithmic profile with blue: $z_0 = 0.2$mm, green: $z_0 = 3$mm, red: $z_0 = 1$m. (a) Vertical wind profiles and (b) the resulting long-term capacity factor. (c) Box plot of the annual capacity factors for the logarithmic profile with $z_0 = 3$mm.

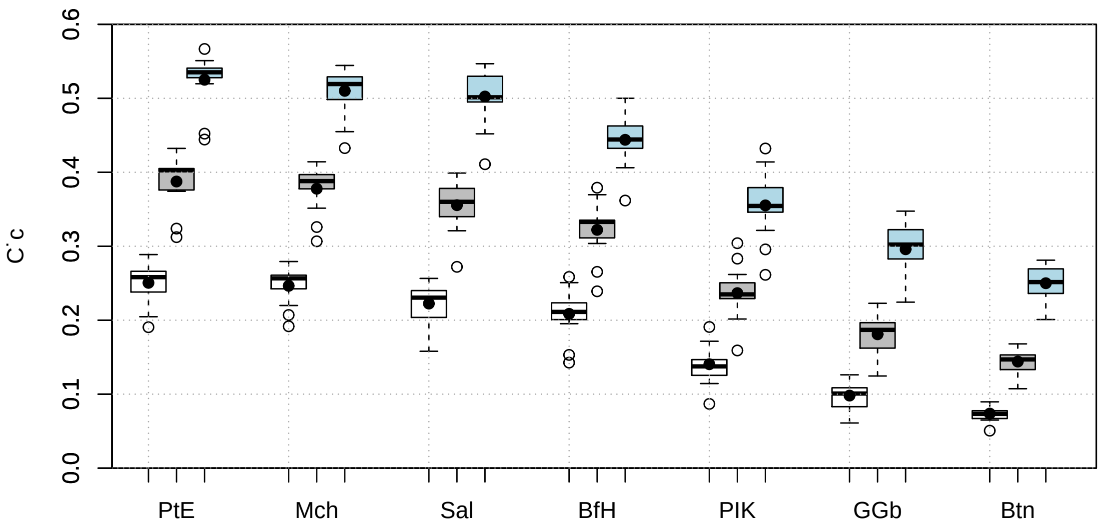

Figure 7: Comparison of the annual statistics for all sites since 1999 between the measurement height of 10 m (clear boxes) and an extrapolated height of 80 m in off-shore conditions (grey boxes) and forested conditions (light blue boxes.

error is

$$\epsilon_C(t, \tau, \delta t) = \frac{1}{\tau} \sum_{t'=t-(\tau-1)}^{t} C_c(t') - C_c(t' + \delta t) \quad (5)$$

this prediction can be made for $M = N - \tau - \delta t$ years in a record of N years, and the absolute prediction error expressed relative to the long-term mean capacity factor, $< C_C >$ is

$$\Delta(\tau, \delta t) = \frac{1}{C_c M} \sum_{t'=\tau}^{N-\delta t} |\epsilon_C(t', \tau, \delta t)|. \quad (6)$$

Since it is useful to know whether predictions tend to be over-optimistic, it is useful to calculate the mean of the error, Δ^+ for those cases where $\epsilon_C > 0$ and vice versa where $\epsilon_C < 0$ to calculate the mean under-prediction, Δ^-. The quantity Δ measures the mean error in the prediction. An alternative and complementary measure of the goodness of a prediction is to calculate the likelihood that the prediction is within a desired error margin. For example, how likely is it that the predictions are within ± 0.02 of the true value, or within 10% of the mean,

$$p\,(|\epsilon| < 10\%) = \quad (7)$$
$$\frac{1}{M}\left\{\text{Number of instances where } \frac{|\epsilon|}{<C_C>} < 0.1\right\}$$

or, to distinguish between the likelihood to over predict or under predict,

$$p\,(0 \leq \epsilon < 10\%) =$$
$$\frac{1}{M}\left\{\text{Number of instances where } 0 \leq \frac{\epsilon}{<C_C>} < 0.1\right\}$$

and

$$p\,(-10\% < \epsilon \leq 0) =$$
$$\frac{1}{M}\left\{\text{Number of instances where } -0.1 < \frac{\epsilon}{<C_C>} \leq 0\right\}?$$

Figure 8 summarises the results from this analysis, where the top row shows the mean prediction errors, Δ and $\Delta^{\pm}$, while the lower row shows the measure of how likely it is that a prediction falls within an acceptable margin of 10%, $p(\epsilon < 10\%)$. The left column shows the analysis against the length of the averaging period from the past, τ, while the right column shows the results against how many years ahead the prediction is made, δt. All plots show the overall result (the open boxes) as well as a differentiation between over-prediction (positive red boxes) and under-prediction (negative blue boxes).

Figure 8(a) shows that the overall mean error is least for very short averaging windows but with a large range in prediction errors. This can be explained by the observation that the large volatility results in an almost equally large likelihood of over predicting or under predicting and that these opposite errors balance each other. As the averaging window is made longer, the mean error increases but the spread of the prediction errors become narrower which suggests that the prediction becomes less a random process but more a systematic but biased prediction. The figure suggests that most consistent prediction is made from an averaging window of 10 to 14 years, beyond which the mean errors remain largely constant but the distributions spread out again. Figure 8(b) illustrates the prediction error in terms of how many years into the future the prediction is made, where the distributions do not differentiate between different averaging windows. While the errors for either under- or over-prediction remains fairly constant, the overall prediction error increases almost linearly with the predictions step which presumably arises from the fact that over-predictions become more prevalent as the prediction horizon is pushed into the future. This means that the further into the future we predict, the more optimistic the prediction.

Figure 8(c) and (d) shows a different measure which might be more appropriate for assessing the risk of using a particular prediction. These plots show the likelihood that the prediction falls within 10% of the actual value, $p(\epsilon < \pm 10\%)$. The spread around the mean likelihood derives from the fact that each averaging window in figure 8(c) contains all possible prediction steps from 1 year ahead to 15 years into the future while each prediction step in figure 8(d) includes predictions form all possible averaging periods from a single year to 20 years. Figure 8(c) shows that the likelihood of making a good prediction of the resource increases consistently with increasing the averaging window up to 10 to 12 years with a typical chance of making a good prediction of around 50%. Beyond this, the likelihood spreads out again and also decreases again. This is confirmed by figure 8(d) which shows that the likelihood of of making a good prediction is around 50% for predictions 3 to 4 years into the future but then deteriorates progressively.

3.4. *Long-term changes in the wind energy potential*

Since there appears to be a systematic drop in the annual capacity factor over the last few decades in Scotland, as demonstrated in figures 3 and 4, or an increasingly large over-estimation of the wind resource as one predicts further into the future, as shown in figure 8(b), the question arises as to whether this is a reflection of ongoing climate change. One interpretation of figure 8(a) and (c) is that the consistent over-prediction is a consequence of an underlying climate shift towards a less windy climate in Scotland, where the magnitude and time scale of that climate shift is such that it emerges as a clear pattern above the inter-annual variability after 10 to 14 years. It is, however, impossible to say whether this climate shift is a gradual and continuing process, or part of a decadal climate cycle, or part of a set of discrete climate changes where one change can be dated to around 1987, one to 2000, and possibly to 2010 and that a future change could happen at any time in either direction (most clearly seen in figure 4).

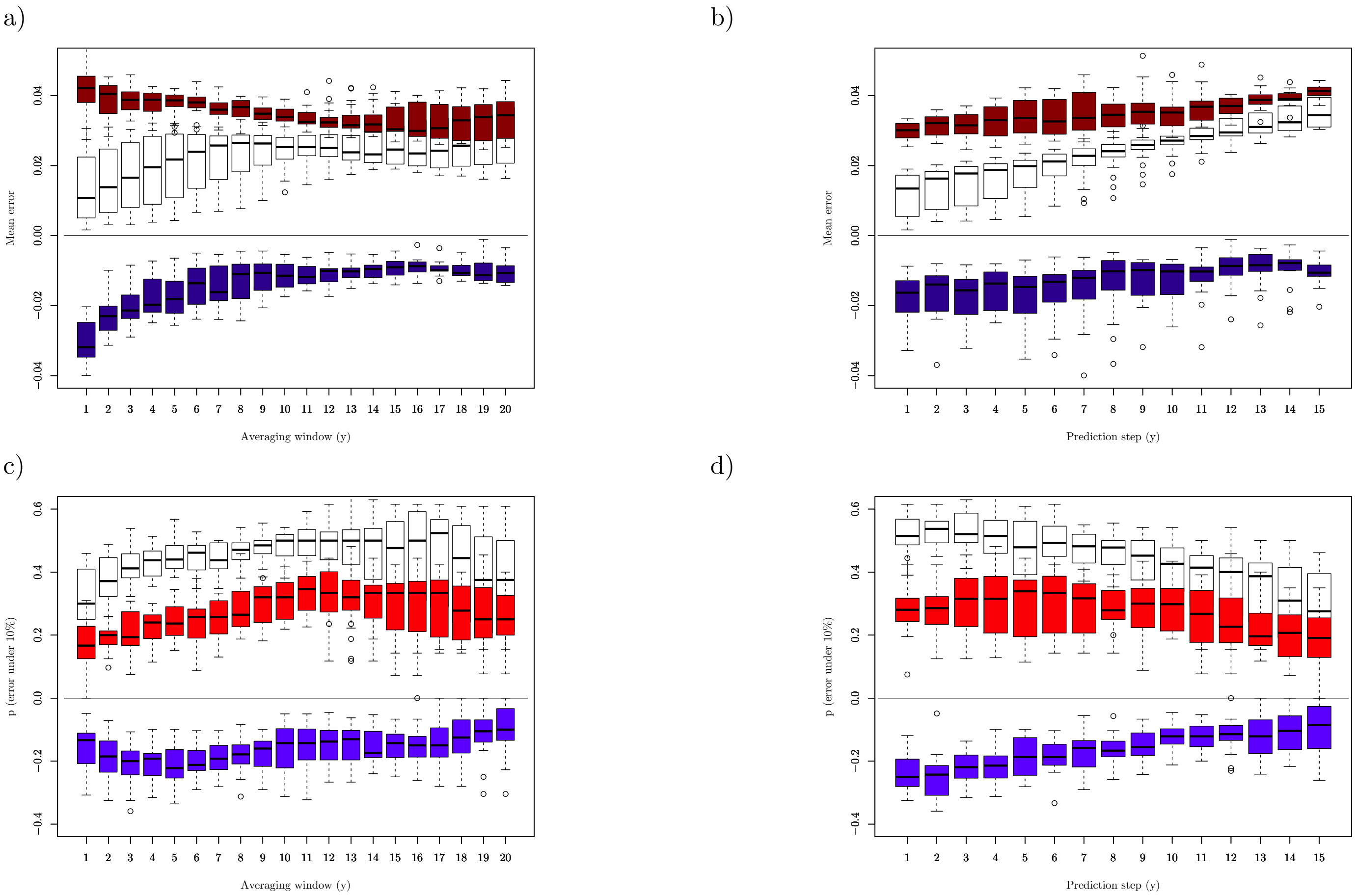

Figure 8: Prediction error for the annual capacity factor; positive row of filled (red) boxes refers to over-prediction, negative (blue) row to under-prediction, and clear row to combined mean. (a) mean prediction error against the length of the averaging window used for the prediction; (b) mean prediction error against the prediction time step; (c) Likelihood to predict the capacity factor to within 10% against the averaging window (d) Likelihood to predict the capacity factor to within 10% against the prediction time step.

3.4.1. Discussion of anemometers

The three longer records are compiled from two different anemometer systems, HWND6910 during the earlier period which were replaced by HCM at Machrihanish (during 1993 while continuing to use the Munro Mk 4 cup anemometer and replacing this by a Vector Mk 6 in 2002) and Blackford Hill (November 2004 while continuing to use the Assman Mk 2 cup anemometer) but by AWSHRLY at Salsburgh (January 2000 and changing from the Munro Mk 4 to the Vector Mk 6 at the same time). All other sites used HCM throughout the periods analysed here. Since the replacement occurred during the decade in which the mean wind speeds seemed to have dropped, it was a concern as to whether the long-term drop in the wind speed might be an instrumental artefact. On concern is the actual height of the anemometer. While it was constant at 10 m at the Blackford Hill site, the anemometer at Machrihanish was initially at 12 m, between 1981 and 1993 at 10m and at 11 m since then. At Salsburgh the anemometer was moved from a height of 8 m to a height of 13 m in 1978 which then reverted to 8 m at the change-over in January 2000. Even though the instrument was not changed at Prestwick, its height was changed from 18 m to 6 m in 2002. At the remaining sites, the anemometer was always at the standard height of 10 m. A first visual inspection of the results did not show any obvious changes except for Salsburgh where there appeared to be a sudden and persistent change of the capacity factors during the change of the instrument or system in 2000.

A second note on the interpretation of the anemometer data concerns the surrounding. Even though the anemometers are positioned in what is referred to as 'open terrain', changes in use of the surrounding land could nevertheless affect how exposed an anemometer is to the wind [28]. The Met. Office's data record specifies the geography type and primary and secondary land use at intervals. While the record is based on somewhat subjective assessments – for example the Bishopton site is listed as 'hilltop' at the beginning, then classified as 'flat' before changing back to 'hilltop' at the next entry– they still can provide some guidance as to whether any substantial change in buildings or vegetation may have affected the anemometers. Certainly, Machrihanish and Port Ellen are constantly associated with primary land use as 'airfield' and secondary use as 'open'. This suggests that the local environment should not result in any noticeable changes. The land use and vegetation surrounding Salsburgh also has not changed appreciatively over the last few decades. Those which might have been affected are Gogarbank, Bishopton, and Blackford Hill as they are in or near the major cities of Scotland which have seen substantial development.

3.4.2. Anemometer trends

To check the results for sensitivity to anemometer height, land use change and instrument change two independent tests were carried out. In one of these tests, the wind speeds were corrected for the different anemometer heights using the logarithmic wind shear profile with a generic surface roughness of $z_0 = 100$mm. To compile these corrected capacity factors into a single data set, the station mean for 2000 to 2009 was removed from each station, similar to the correction carried out by Watson and Kritharas[28].

As the surface roughness for the various sites is not known, a second test was performed which only used the data themselves and the known time at which alterations were made. In this test, a linear regression of the annual, un-corrected capacity factor time series was applied to each section separately, corresponding to each instrument or height. If each section from a station gave a gradient of the linear fit which was consistent with the gradients from the other sections of the same site, a composite site record was created by shifting the results by the difference in intercept across the change.

Table 3 shows the slopes of the linear models for the individual station sections, for the stations compiled from adjusted sections, and for the combined records. This allows to estimate as to whether any particular station might have suffered from effects other than instrument height, such as changing vegetation. Only three sites had records long enough to be compiled from different instruments. Two of these, Machrihanish in the West and Blackford Hill in the East, show internally consistent trends. The central station, Salsburgh, presents a different picture. Not only was the change-over to the AWSHRLY associated with a noticeable jump in the mean wind capacity factor but also in the linear trend before and after the change. While the later record suggested a decrease of the mean capacity factor consistent with the other sites (though the linear model for these data was not statistically significant), the earlier record did not show any significant linear trend.

From these figures one can conclude that the wind speed data from Salsburgh should be viewed with a certain amount of reservation. It is not clear from the information available as to whether the inherent uncertainty in this record was caused by one of the specific instruments used or by slightly different positioning of the two anemometers. In any case, a more general recommendation is that long-term records compiled from different instruments should be analysed for internal consistency. Given the uncertainty surrounding this station, it was excluded from the further analysis.

The adjusted station records for the other two stations are listed together with the full records from the more recent stations in the second part of table 3. As can be seen, the slopes of the full station results are entirely consistent with each section and, as the statistics could be carried out on more data, the significance and explanation of variance is much improved. Each of the stations presented in table 3 shows a decreasing trend, though the magnitude of the trend varies somewhat across the stations. Their significance level appears to be strongly linked to the length of the available record.

In the final step of this analysis the records from all six remaining sites are combined into a composite regional

Table 3: Summary of the key linear model results for the individual stations, subdivided into old instrument and new instrument where appropriate and the composite data. (Stars denote level of significance).

Station Name		slope C_c year^{-1}	± slope	r^2	Significance	
Machrihanish	old	−0.0023	±0.0011	0.17	0.055	.
	new	−0.0023	±0.0011	0.22	0.053	.
Salsburgh	old	+0.0006	±0.0018	< 0.01	0.7	
	new	−0.0018	±0.0021	0.07	0.4	
Blackford Hill	old	−0.0026	±0.0009	0.23	< 0.01	**
	new	−0.0024	±0.0049	0.04	0.7	
Port Ellen		−0.0048	±0.0015	0.46	0.007	**
Machrihanish		−0.0023	±0.0004	0.46	$< 10^{-6}$	***
Prestwick Gannet		−0.0042	±0.0013	0.43	0.0055	**
Bishopton		−0.0014	±0.0007	0.25	0.08	.
Gogarbank		−0.0024	±0.0015	0.17	0.14	
Blackford Hill		−0.0026	±0.0006	0.34	< 0.0002	***
Combined, height-corrected		−0.0017	±0.0002	0.29	$< 10^{-10}$	***
Combined, empirical		−0.0023	±0.0002	0.43	$< 10^{-15}$	***

record using the two correction approaches, shown in the third part of table 3. Correcting each section by the known height of the anemometer and then removing the 2000-2009 decadal mean for each station resulted in a composite capacity factor data set which showed a decrease in capacity factor of between −0.015 and −0.019 per decade. Using the empirical correction of shifting sections by the intercept and also removing the decadal mean gave a decrease in capacity factor of between −0.021 and −0.025 per decade.

If the significance and explanation of variance are taken as a guide, the empirical correction performs better than the wind shear correction for these data. This might suggest that either the assumption of a common wind shear profile across the site was too simplistic, or that other anemometer characteristics in addition to their height contribute to bias in readings.

Keeping the overall uncertainty in approach or incorporated factors in mind, the expected trends would be a reduction in capacity factor by between 0.0015 and 0.0025 per year. In fact, the majority of the results are between 0.0023 and 0.0026 – closer to the result using the empirical adjustment across instruments rather than the imposed height adjustment using an assumed wind shear profile. Of those outwith that range, the three sites that have a significant trend, and a reasonable explanation of variance, have a much more pronounced decrease of capacity factor, namely between 0.0033 and 0.0048 per year; these sites are Port Ellen, Prestwick, and Salsburgh – three very different sites in terms of length of record, location, and surrounding land use.

Taking all these factors together still points to a persistent decrease of the wind resource in Central Scotland at a rate of around 0.002 per year or around 5% over a decade at the better sites. This decrease is consistent with the trend presented by Watson and Kritharas [28] for the North West. In addition to their observations, we found that not only surrounding land change and anemometer height could affect the readings but the characteristics of the instruments themselves. At present, a correction for an instrument change can only be based on an empirical matching of some statistics across the instrument change. In this analysis, this was done through adding an offset calculated from the difference in the observed linear trends for the distinct records from the two instruments.

3.4.3. Test of climate change

Assuming that the electricity output since 1999 was from a stationary time series, the boxplots in figure 3(b) indicated that the year 2010 can indeed be classified as an outlier for five out of the seven sites and figure 4. However, the linear models for the various sections of the long records indicate that there is likely to be a long-term decrease in the wind energy potential.

One immediate observation from figure 9 (a) is that the different sites show very similar differences from their respective mean for the period from 1989 until the present but that there is considerable scatter for the earlier periods which could either reflect a more variable climate or less reliable instruments in the earlier part of the record. The residuals, in figure 9(b), suggest that there may be a decadal oscillation within the system, with low-wind periods in the early 70s, mid 80s, early 2000s and most recently. These residuals seem to have a relatively stable magnitude of around ±0.05. This suggests that 2010 was still a year with a consistent negative residual for all sites, but that the magnitude of the residuals is now well within the generally observed range. This fact has to be taken together with the global linear model of a decreasing wind climate seen consistently across the region.

4. Discussion

In this section, the observations from section 3 will be reviewed. First, the general level of variability and the sensitivity of local variation to electricity output will be discussed, drawing on sections 3.1 and 3.2. Following on from the discussion of the inter-annual variability, the discussion will move onto the decadal time scale and discuss the issues responses in wind energy production to climate change and the resource prediction, drawing on the observations from sections 3.3 and 3.4.

4.1. Sensitivity and interannual variability

Large and small wind energy systems operate under very different conditions of which only one particular aspect was analysed here, namely the wind speed. Large wind farms use turbines with hubs typically higher than 60 m above ground where the wind speed is significantly higher than near the ground. Wind speeds at good sites extrapolated to 80 m have the potential to operate reliably at capacity factors in excess of 30% and may even achieve 40% where the typical relative variability as quantified by the standard deviation is 10% to 15%. Compared with capacity factors reported for well-designed operating wind farms in good locations, the range of $30-40\%$ is still very optimistic.

Several factors will reduce the actual output from the ideal levels calculated here. The most obvious factors affecting a wind farm's performance will include turbine yaw, wake effects, and turbine availability. Some wind direction changes will either occur on a time scale shorter than the yaw control and the turbine will not respond at all to them. Other wind direction changes will continue into the response time of the turbine and these will lead to a delay between the wind direction change and the turbine response. Both cases will result in sub-optimal performance of the turbine, probably reducing the average performance by a few percent. On top of these are planned and unplanned maintenance or service periods reducing the availability of turbines. An approximate but realistic overall reduction in the output from a large turbine in a year might be by around 10%. If these intra-annual effects are combined with the inter-annual volatility of the resource of, on average 11%, one could expect are a more realistic capacity factor for the good sites in central Scotland of between 32 and 38% at the Atlantic coast. The corresponding expectations for exposed inland sites would be between 27 and 33%.

A further effect in wind farms with many turbines is that some turbines will inevitably operate within the wake of an upstream turbine. An analysis of an offshore farm suggested that the performance of turbines inside a wind farm may be reduced to a level of around 60% compared to the turbines in the front row facing the wind [36]. The potential magnitude of this effect on the overall output from a wind farm is the motivation for active research in wake modelling, e.g. [37].

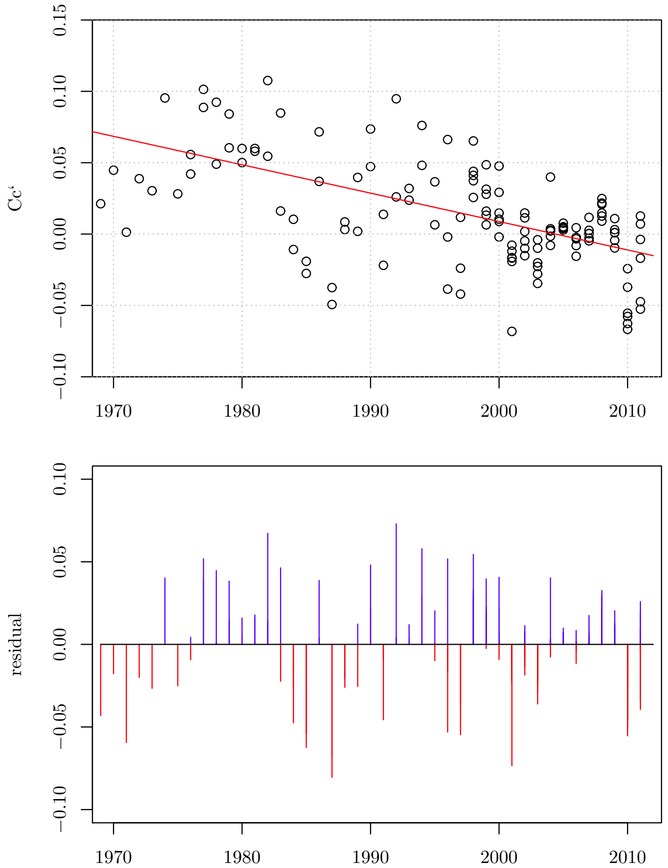

Figure 9: Fit of linear model to change in capacity factor against the 10-year mean of 2000 to 2009.

Small wind turbines, operating with hub heights of around 10 m or even less, not only operate under much reduced mean wind conditions but also under relatively much larger inter-annual fluctuations of around 20%. This is furthermore compounded by much larger fast fluctuation in both wind gusts and wind direction. This will lead to a further reduction in overall productivity, especially of turbines relying on a yawing mechanism. Depending on the location of the turbine and its performance characteristics, the results shown above in figure 3 for ideal turbines might be reduced by 50% or even more, leading to expected capacity factors in exposed coastal sites of possibly around 15%, maybe around 10% at good inland locations but as little as 3 to 5% in more sheltered areas. The latter figures align well with the Energy Saving Trust survey [6], and the 10% figure aligns well with a reported performance of a 2.5kW Proven turbine on the Newberry Tower at the Glasgow School of Art on the crest of Garnethill in the city of Glasgow. Considering the strong effect of yaw error, vertical-axis turbines may actually be more productive than horizontal-axis turbines in near-ground wind conditions despite their lower conversion efficiency.

4.2. Long-term wind trend and resource prediction

The analysis in section 3.3 suggested that using a period of 10 to 14 years provides the most reliable estimate of the current wind climate, and that this can be used to predict the wind climate with a 50% chance to predict it correctly within 10%. This was complemented by the result from fitting a linear model to the capacity factor from all sites that it has decreased over the last 43 years with a slope in the capacity factor of between -0.0015 and -0.0025 per year. Obviously, the climate system is not a linear system, and figures 3 and 4 clearly show that the changes are not gradual but appear at present more step-like underlying the much stronger year-to-year volatility. Given that this analysis is only based on the local wind record and does not rely on climate models or on observations of supra-regional climate indicators such as the North Atlantic Oscillation index, this analysis does not claim to identify climate change but it does point to the real possibility that the local wind climate does change on a decadal time scale and that these changes can be fairly abrupt by the observation of some key years in which the wind resource or capacity factor changed dramatically without recovering to the same levels observed prior to that year.

Using the linear model as a first guide to quantify a possible change in the resource, the year 2010, which was described to be an 'unusually calm year' cannot be identified as an exception when seen as part of the overall climate drift over the last four decades towards a lower wind energy climate even though the following year has shown some recovery in terms of wind energy production potential in central Scotland.

This insight then suggests that it might be beneficial to use a linear model from the recent past to predict the near future more reliably. Based on this assumption, the resource prediction, initially assuming a stationary or persistent climate and presented in section 3.3, was repeated using a linear model based on the last ten years to predict the next mean capacity factor or wind over the next five years. This analysis is summarised and compared against the prediction assuming persistence in figure 10 for the example of Machrihanish using the 10 m height data. Figure 10(a) shows the actual prediction error made by either method, 'persistence' or 'linear model'. This not only demonstrates that the earlier period showed a much higher variability and possibility for wrong predictions than the later half of the period but it also shows that while the linear model may be highly significant it cannot be used to make accurate predictions since the magnitude of the decadal change from the linear model (around -0.02) is still less than the volatility of the system. This means that if we get the slope wrong the prediction error is actually magnified. Figure 10(b) shows the likelihood of making an acceptable prediction with a specified error margin, the same quantity as in figure 8(c) and (d) but here against varying the acceptable error margin from 0.5% to 10%, where the open circles refer to the prediction using persistence and the filled circles to the predictions from the 10-year linear models. In line with the observations from figure 10(a), the persistence assumption is more likely to return an acceptable prediction with a predictive power of being able to predict the next five years to within 10% with chance of almost 80% whereas the linear model is only half as good.

In short, we observe the apparent paradox that at a decadal time scale, the volatility overwhelms the signal and renders linear predictions useless but that persistence introduces a clear bias at the longer time scale of several decades, where the linear model shows a good fit to the data. This apparent paradox can be used to guide wind farm developers in choosing the appropriate period on which to base their resource assessment on but then assume that this appropriate period does reflect a stationary climate to a good degree and can be used to predict the resource for a similar period ahead.

5. Conclusions

In this study, long records of wind speeds from UK Met. Office surface stations in Scotland were analysed in the context of their spatial and temporal variability, where the winds were converted to a capacity factor from a typical turbine performance curve.

The main findings underline the importance of siting turbines in good wind resources as the electricity output is very sensitive to small changes in the mean wind, especially in the poorer sites. They also highlight that the year-to-year variation in the expected output typically varies in the Scottish climate by 10 to 15% with the possibility of much larger changes in individual years. Despite this, the analysis has confirmed that sites at the west coast of Scot-

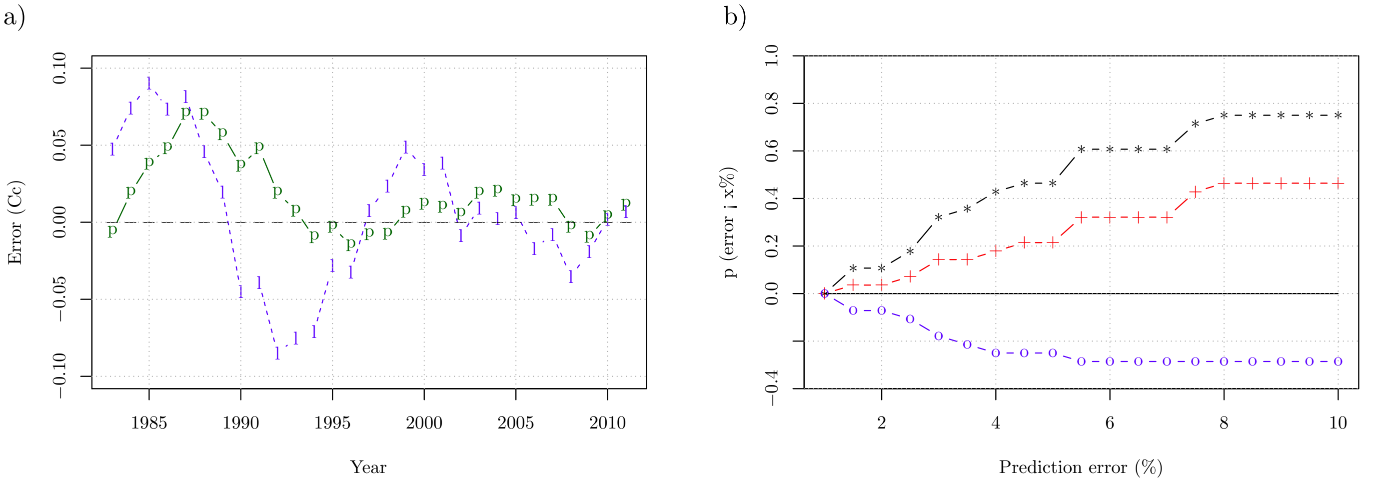

Figure 10: Predicting the annual capacity factor for the next 5 years based on the previous 10 years at Machrihanish. (a) Prediction error against year of prediction using either persistence 'p' or a linear model 'l', (b) Likelihood of predicting the next five years within a given error margin against that specified error margin using persistence (open circles) or a linear model (filled circles)

land or at exposed places across the country have a very good wind resource.

On the time scale of the available wind records of 43 years at one site, it has been shown that the wind resource has significantly decreased and that the decrease appears to have happened in a few discrete steps which had been masked by the large volatility of the wind climate. One of the conclusions from this is that the year 2010, which some had described as an unusually calm year does actually fit into the overall trend. This observation highlights a serious need to continue to investigate the link between climate indicators and wind observations.

Since the long-term climate drift is not progressing in a gradual, linear fashion but in almost discrete steps of variable duration, the insight that the climate is changing cannot be used to build a predictive model based on a gradual drift. Despite this, the analysis of the climate in terms of the slow drift can be used to identify reliable wind climate periods during which the climate can be taken as stationary. These almost stationary windows can then be used to make reliable prediction for the near future on a similar time scale as the length of the window.

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